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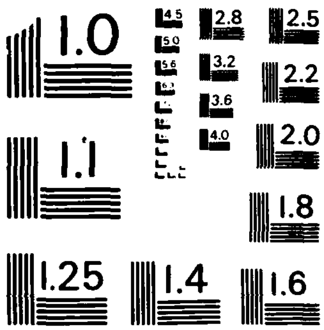

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BLACK/WHITE DIFFERENCES IN THE PREDICTION
OF SUCCESS IN AIR FORCE AND MARINE CORPS
TECHNICAL TRAINING PROGRAMS

Walter M. Houston
and
Melvin R. Novick

ONR Technical Report 85-8

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20. Abstract continued

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Black/White Differences in the Prediction of Success in Air Force and Marine Corps Technical Training Programs*

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Abstract

Johnson-Neyman methodology is used to investigate differential prediction by race in Marine Corps and Air Force occupational specialty areas. For the Air Force data set, meaningful Johnson-Neyman regions of differences were found in 23 of 28 comparisons. In all cases the regressions for blacks were flatter than for whites and the black/white interaction was disordinal. In 12 cases the cut-score for course qualification was within the Johnson-Neyman region and in 10 of the 12 cases the bias was negative for blacks. It is also noted that if the cut-scores had been set substantially higher the bias would have been positive for blacks in all cases. It is suggested that this analysis explains why earlier studies which averaged bias across values of x yielded mixed results. It is also suggested that the consistent result obtained here results from the lower predictability found in the black subpopulation.

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Black/White Differences in the Prediction of Success in Air Force and Marine Corps Technical Training Programs

Introduction

The investigation of differences between groups in the criterion-related validity of test scores can be conducted with correlation coefficients (differential validity) or with regression parameters (differential prediction). Differential validity refers to the possibility that criterion-related validity coefficients may differ among identifiable groups in the population. Differential prediction refers to the possibility that regression equations may differ among these groups. According to the Standards for Educational and Psychological Testing (1985), "there is differential prediction, and there may be selection bias, if different algorithms (e.g. regression lines) are derived for different groups and if these predictions lead to decisions regarding people from the individual groups that are systematically different from those decisions obtained from the algorithm based on the pooled groups (p. 12)." Equality of correlations in two groups does not necessarily imply identity of prediction. This investigation was concerned with differential prediction by race for Air Force and Marine Corps technical training programs.

Traditional methodology for comparison of regression equations involves testing null hypotheses of equal within-group slopes, y-intercepts, and less frequently, residual variances (Gulliksen and Wilks, 1950). Our position is that when the emphasis of an investigation is on assessing the importance of differences in predictions for selection

decisions, such statistical tests are largely uninformative. Two regression equations may differ significantly in slopes and/or y-intercepts, and yet yield near-identical criterion predictions when evaluated within particular intervals on the predictor score scale. Conversely, failure to reject the overall null hypothesis of identical slopes and/or y-intercepts does not imply that there will not be important differences in the criterion predictions obtained from the within-group regression equations along some portion of the predictor score scale. Finally, the methodological complexities arising when testing a null hypothesis for slope but not intercept, intercept but not slope, the delicacy of interpretation in all cases of rejection and the differences in power between the two tests, make the standard procedures unattractive. Therefore, in the comparison of regression lines relative to possible predictive or selection bias, the most important and useful comparison to make is that of criterion predictions obtained from the regression equations evaluated at crucial points along the x axis. Typically in selection contexts, the point at which to compare the regression equations is at and near the cut-off value on the predictor score scale required for admission into the course or training program. One way to do this is to follow the methodology of Johnson and Neyman (1936) and define intervals on the predictor axis throughout which the null hypothesis of coincidence of regression functions is rejected and then to compare these intervals with the x-value cut scores. If important points on the x-scale fall within the Johnson-Neyman interval then differences in y values at those points should be studied.

This paper addresses the general issue of differential prediction for blacks and whites by means of a detailed analysis of selected military training courses within both the United States Marine Corps and the United States Air Force. The analyses were conducted within training course. The primary concern was the identification of differences between predicted training success for blacks and whites based on the Armed Services Vocational Aptitude Battery (ASVAB Forms 8/9/10) composite scores and subtests typically used for selection. Our objectives in this paper were to address the substantive issue of possible bias in prediction and selection in current Air Force and Marine Corps procedures and the larger substantive and methodological issues involved in race-related differential prediction studies. This paper follows closely the methodology exhibited in Gamache and Novick (1985) and Dunbar and Novick (1985).

Method

Data Source

Data available for this investigation were obtained from the administration of the Armed Services Vocational Aptitude Battery (ASVAB), Forms 8, 9, and 10, to Air Force and Marine Corps recruits who subsequently attended a variety of training courses at military bases located throughout the United States. Military training courses in both the Air Force and Marine Corps are placed into training specialty groups in an attempt to form homogeneous groups of courses and jobs that require similar skills. A common ASVAB selector composite is used to establish minimum prerequisites

for training courses within a particular training group. Different training groups utilize different selector composites.

Predictor variables of interest in this investigation are the ASVAB composites used for selection and the individual ASVAB subtests from which the composites are constructed. The structure of the ASVAB selector composites used by the Air Force and Marines Corps are detailed in Table 1. All ASVAB composites are unit weight composites of the ASVAB subtests, except for Air Force Mechanical, which uses an integer weight composite of subtests.

Insert Table 1 about here

All ASVAB subtests are converted to a standard score scale with a mean of 50 and standard deviation of 10 in the 1980 reference population (Maier and Sims, 1982) before the composites are formed.

Procedures for computing the aptitude composites differ between the Marine Corps and the Air Force. The Marine Corps converts the sum of the subtest standard scores to a standard score scale with a mean of 100 and a standard deviation of 20. The Air Force uses percentile scores, with the sum of the subtest standard scores converted directly to percentile scores in the reference population. The criterion variable is the final course grade (FCG) in the training course, with values on the FCG variable falling between 70 and 100 for most training courses.

The military training courses chosen for analysis, along with the prerequisite on the ASVAB composite required for admittance into the course, and sample sizes are presented in Table 2A and Table 2B for the Air Force and Marine Corps data sets, respectively.

Insert Table 2A and Table 2B about here

For the Air Force data, 23 different courses in four specialty groups with sample sizes in excess of 100 were available for the analysis. Out of these 23 courses, 5 courses have double (e.g. AIA=50 or AIG=45, or AIE=30 and AIM=35) selector composites. The proportion of the sample within each training course that is black ranges from .10 to .36. For the Marine Corps data, 3 courses had sample sizes in excess of 100 and 2 courses had sample sizes ranging between 50 and 99. For these data, the proportion of the sample within course that is black ranges from .13 to .32.

Procedure

Utilizing Bayesian simple linear regression analyses and employing non-informative prior distributions, within-group posterior distributions on the slope, the y-intercept at x=0, and the residual standard deviation were determined for the regression of FCG on the appropriate ASVAB selector composite and for the regression of FCG on each of the subtests of which the composite is composed. In this case, ASVAB variables have been

considered as single predictors of training success. The subtests from which the selector composites are constructed were also considered as multiple predictors of training success. While these data are subject to the effects of restriction of range on the independent variables, no attempt to remove these effects were considered in this study. Also, this investigation did not take into account the administrative and self-selection into training courses that was almost certainly present.

Regions along the predictor score scale where potentially important differences existed between the within-course race-differentiated regression functions were identified using the Johnson-Neyman technique. This technique assesses differences in the regression equations as a function of X by identifying that subset of x values for which the 100(1 - a)% credibility or confidence interval for the difference in predicted criterion scores does not include zero. The equivalence of classical and Bayesian Johnson-Neyman analyses, for non-informative priors, one predictor variable, and under an assumption of equal residual variances, is shown in Appendix A. A distinction between 'simultaneous' and 'nonsimultaneous' regions of rejection is sometimes made in the methodological literature surrounding uses of the Johnson-Neyman technique (see, for example, Potthoff, 1964; Potthoff, 1983; and Rogosa, 1981). Potthoff (1964) claims that simultaneous regions are appropriate for making statements about the difference between regressions over the entire range of x and that a nonsimultaneous region can be validly used to make a statement about the difference between the regressions at a single x value. The results presented in Appendix A verify that, from a Bayesian point of view, nonsimultaneous regions are appropriate when comparing two regression lines

over the entire range of x or at particular points along the abscissa. Using the observed predictor distributions and regions identified by the Johnson-Neyman analyses, the proportion of each sample that might be affected by differential prediction was determined, and is given in Tables 5A and 5B.

While the Johnson-Neyman technique identifies regions on the predictor score scale where differences between regression equations exist, the technique gives no indication of either the direction or magnitude of differences in criterion predictions. For training courses in which the current or proposed cut-o t level on the appropriate ASVAB selector composite fell within the Johnson-Neyman region of significance, differences in the criterion predictions obtained from the within-group regression lines evaluated at the cut-off value on the relevant ASVAB selector composite were examined in greater detail to determine both the direction and magnitude of the observed differences. Differences in predicted FCG obtained from the race-differentiated regression equations evaluated at specific points along the predictor score scale were also examined to determine the direction and magnitude of differential prediction within each training course, and are given in Tables 9A and 9B.

Results

The sufficient statistics for the within-group single predictor regression analyses for both the Air Force and Marine Corps training courses are reported in Table 3A and Table 3B, respectively. In each

table, the training courses have been subclassified according to training group.

Insert Table 3A and Table 3B about here

Table 3A indicates a consistent trend for blacks to have lower means on the selector composites. This trend holds for every training course presented in Table 3A. The largest mean differences were observed within the Mechanical Specialty, where mean differences between whites and blacks ranged from 12.1 to 24.9 scaled score points, with whites scoring an average of 13.9 points higher than blacks across the nine courses. Expressed in black standard deviation units, mean differences between whites and blacks ranged from 1.1 to 1.4, with whites scoring an average of 1.2 black standard deviation units higher than blacks across the nine courses. Black standard deviations on the selector composites tend to be smaller than those for whites. Although in the same direction, mean differences on the criterion tend to be much less pronounced. Table 3A also indicates that the observed correlation for blacks between FCG and the selector composite is less than the correlation observed for whites in every training course. Reduced correlations for blacks between FCG and the subtests from which the composites are constructed are also evident. Observe from Table 3B that mean differences between blacks and whites on the selector composites and criterion variable are much smaller than the differences observed in the Air Force training courses.

The results of the within-group single predictor regression analyses are reported in Table 4A and Table 4B, which contain the means of the marginal posterior distributions on the slopes, y intercepts at x = 0, and residual standard deviations for each training course in the Air Force and Marine Corps data sets, respectively.

Insert Table 4A and Table 4B about here

Inspection of the regression parameter estimates in Table 4A indicate that the regression of FCG on the appropriate ASVAB selector composite and on each of the subtests of which the composite is constructed tend to yield regression lines for whites that have larger slopes and smaller y intercepts at x equal to zero than the regression lines obtained for blacks. This tendency is remarkable in its consistency across training courses, specialty groups, and predictor variables. Another interesting feature of these data is that the within-course race-differentiated regression lines for the regression of FCG on the relevant selector composite tend to intersect within the range of the data under all circumstances. The point on the abscissa where the race-differentiated regression lines intersect is presented in column 3 of Table 5A and Table 5B. This disordinal interaction between Race and the observed regression lines when using the appropriate selector composite as the sole predictor is particularly evident for courses in the Administrative, Electronics, and Mechanical Specialties. For courses within these specialties, every one of the race-differentiated regression lines intersects within the range of the

data. The intersection of race-differentiated regression lines is also present when the subtests from which the composites are constructed are considered as sole predictors of training success. The disordinal interaction between Race and the observed regression lines, coupled with the larger slopes and smaller y intercepts at $x = 0$ of the white regression lines, demonstrates that the criterion performance of blacks may be systematically underpredicted at the lower end of the predictor score scale and systematically overpredicted at the upper end of the predictor score scale when a pooled regression equation is used. For these data the overall effect, taking into account the value of the cut-score, is one of underprediction of black criterion performance. In other instances whether or not one finds over or under prediction in a particular situation might depend in part on the distribution of x values and on the cut score.

The comparison of within-group regression equations in terms of slopes and intercepts permits the investigation of the possibility that systematic errors may occur in predicting the criterion performance of the groups when a pooled regression equation is used. On the other hand, differences between groups in residual standard deviations imply that the magnitude of nonsystematic errors of prediction tends to be larger for members of one group than for members of another group. Table 4A indicates that the differences between within-group residual standard deviations are not consistent and are quite small. In this case, the effect of a pooled regression equation on nonsystematic errors of prediction is negligible. Inspection of the regression parameter estimates in Table 4B reveals no clear-cut trends.

Results of the Johnson-Neyman analyses, for a difference of zero and an 'alpha' level of .1, are reported in Table 5A and Table 5B.

Insert Table 5A and Table 5B about here

This technique identifies regions on each predictor score scale where the 90% credibility interval for the difference in criterion predictions does not include zero. Also presented in Table 5A and Table 5B are the proportions of the total sample and black sample potentially affected by the observed differences in criterion predictions. As shown in Table 5A, the Johnson-Neyman region of rejection for the appropriate ASVAB selector composite was the null set in only five training courses. The weighted average proportion of blacks with test scores in the Johnson-Neyman region (with black sample sizes used as weights) was largest for courses in the Administrative specialty (.66) and smallest for courses in the Electronics specialty (.34). Substantial differences in criterion predictions were also found when the subtests from which the composites are constructed were considered as single predictors of training success. For 3 out of the 5 training courses in the Marine Corps data set presented in Table 5B, the Johnson-Neyman region of rejection for the relevant selector composite was the null set.

For training courses in which the current or proposed cut-off level on the appropriate selector composite fell within the Johnson-Neyman region of rejection, Table 6 reports the mean and 90% credibility interval for the

difference in criterion predictions obtained from the race-differentiated regression lines evaluated at the cut-off level on the selector composite. Those differences in criterion predictions with positive means indicate overprediction of black criterion performance and those with negative means indicate underprediction of black criterion performance when a pooled regression equation is used.

Insert Table 6 about here

For the 12 courses in the Air Force data set for which the cut-off level on the selector composite fell within the Johnson-Neyman region of rejection, black performance was underpredicted (negative bias) in 10 courses and overpredicted in 2 courses (positive bias). Expressed in black standard deviation units, the underprediction of black performance ranged from -.08 to -.68, while the overprediction of black performance ranged from .14 to .27. A comparison of Table 6 with column 3 of Table 5A indicates that the cut score on the appropriate ASVAB composite required for admittance into the training course is less than the point of intersection of the regression lines, indicating some degree of negative selection bias for blacks. For the 2 courses in the Marine Corps data set in which the Johnson-Neyman analyses indicated the presence of differential prediction at the cut-off level on the selector composite, the distributions presented in Table 6 indicate overprediction of black

criterion performance in each course. The amount of overprediction was .27 to .43 black standard deviation units.

The subtests from which the selector composites are constructed were also considered as multiple predictors of training success. The estimated regression parameters for these full regression models, obtained by the regression of FCG on the subtests, race, and race-subtest interactions are presented in Table 7A and Table 7B for the training courses in the Air Force and Marine Corps data sets, respectively. Table 7A and Table 7B also contain standard errors of estimate and squared multiple correlation coefficients.

Insert table 7A and Table 7B about here

Notice from Table 7A that the white-black grouping variable receives a negative weight in 27 out of 28 courses, even after the effects of the interaction terms are considered. With blacks and whites coded 0 and 1, respectively, these results indicate, after all subtests are used as predictors, that black performance on the criterion to be, in some cases, substantially higher than would be predicted using white regression equations for the individual subtests. Table 7A also indicates that the squared multiple correlation coefficients for blacks are smaller than for whites in every training course. Differences between white and black within-course multiple regressions expected to be stable over sampling are presented in Table 8, which contains the results of testing the null

hypothesis of coincident regressions. The null hypothesis of coincident regressions was rejected in 5 out of 10 courses within the General specialty and was rejected in 5 out of 9 courses within the Mechanical specialty.

Insert Table 8 about here

Table 9A and Table 9B report differences in criterion predictions, expressed in black standard deviation units, obtained from the race-differentiated regression equations evaluated at one standard deviation below the mean, the mean, and one standard deviation above the mean of the within-course, black predictor distributions for each of the single predictors and for the multiple subtest predictors. Negative values indicate underprediction of black criterion performance, while positive values indicate overprediction. The results presented in Table 9A are consistent with the observed trends for the race-differentiated regression lines to intersect within the range of the data, with the black regression lines having smaller slopes and larger y intercepts. Underprediction of black training success is more frequent when the lines are compared at a lower point on the predictor score scale, and overprediction of black training success is more frequent when the regression lines are compared at higher points on the predictor score scale.

Insert Table 9A and Table 9B about here

In order to control for the possible confounding of sex and high school achievement with race, the analyses of the Air Force data set were repeated for a restricted sample of male, high school graduates. Although not reported here, these analyses yielded results very similar to the results presented above. Dunbar and Novick (1985) reported a reduction in differential prediction between male and female Marine Corps recruits in the Clerical Specialty when information about the receipt of a high school diploma was utilized. In an attempt to replicate the findings of Dunbar and Novick (1985) in the present context of race-differentiated prediction, the Marine Corp data were reanalyzed for a restricted group of male recruits with high school diplomas. The results of these analyses were inconclusive. No meaningful reduction was found. The Johnson-Neyman technique applied to the high school sample identified regions on the same two training courses for which regions were identified using the total sample. The proportions of recruits potentially affected by contrasting race-differentiated regressions were slightly smaller than the corresponding proportions obtained when using the total sample.

Conclusion

Differential prediction by race is affirmed, but shown to be highly dependent on the cut score. The consistent finding is that of lower slopes and higher y intercepts at x equal to zero for blacks. In summarizing the research into race-differentiated prediction in both academic and employment settings, Linn (1982) noted the tendency for the slope to be somewhat less for blacks than whites in most of these studies. Also, a disordinal interaction between race and the observed regression lines was found for a majority of training courses. The consistent finding of lower slopes for blacks and the intersection of the race-differentiated regression lines within the range of the data show that the bias for blacks will be negative for lower cut scores when a common regression is employed, while the bias for blacks will be positive for higher cut scores. Thus, the relative advantage or disadvantage that may result from differential prediction depends upon both the selection rule employed and the distribution of predictor scores in the minority group. A distinction needs to be made between bias at particular points on the predictor score scale (i.e. at the cut-off point) and the average bias which occurs over the range of the predictor score scale. Due to the lower slopes for blacks and the intersection of the race-differentiated regression lines within the range of the data, black performance may be underpredicted at the cut-score using a pooled equation and yet, on the average, the pooled equation may yield overpredictions for blacks. To conclude that the use of a pooled regression equation tends to overpredict the criterion performance of blacks can be highly misleading when the conclusion is based on the bias

averaged over the entire range of the predictor score scale. With the current and proposed cut-scores used in the present application, bias at the cut-score is negative for blacks in a majority of cases in this study where differential prediction was observed. As indicated earlier the degree of negative bias ranges from .08 to .68 for those courses in which a significant difference was found. The higher number is of some concern but it is atypical and undoubtedly involves sampling error. Considering that statistical significance was found in only 12 of 23 cases it seems evident that the overall average negative bias is low, probably about .25 standard deviations. Furthermore it seems clear that at the present cut-score very few blacks are being outselected as a result of this negative bias.

Going beyond this particular study and adding to the findings summarized in Linn (1982) it seems that, generally, an increase in the cut-score will reduce bias against blacks and would result in bias in favor of blacks for high cut-scores.

Discussion

In addition to the work reported above attempts were made to reduce race-based differential prediction by altering the choice of subtests as in Dunbar and Novick (1985) and the choice of weights as in Dunbar, Mayekawa, and Novick (1985). These attempts were not successful. Our conclusion is that such methods have little to offer for the study of race-differentiated prediction.

It is the view of the present authors that race-differentiated prediction is primarily a function of the lower predictability found for

black groups which results in flatter regression functions. The degree of adverse impact and differential prediction depends heavily on the relationship between the cut-score and the intersection point for the two regression lines. As a result no general statement concerning race-based differential prediction is possible. The best that can be said is that if the cut-score is low selection bias against blacks will be higher than if the cut-score is high. On the other hand the corresponding adverse impact increases with cut-score.

Acknowledgment

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Table 1

The Structure of ASVAB 8/9/10 Selector Composites

Air Force

Composite	Abbreviation	Subtests
Administrative	AIA	VE + NO + CS
Electronic	AIE	AR + MK + EI + GS
General	AIG	VE + AR
Mechanical	AIM	MC + GS + 2 * AS

Marine Corps

Composite	Abbreviation	Subtests
Clerical	CL	VE + NO + CS
Electronics	EL	AR + MK + EI + GS
General-Technical	GT	VE + AR

Subtests

AR = Arithmetic Reasoning
AS = Auto and Shop Information
CS = Coding Speed
EI = Electronics Information
GS = General Science
MC = Mechanical Comprehension
MK = Mathematics Knowledge
NO = Numerical Operations
VE = Verbal

Table 2A

Training Courses, Sample Sizes, and Minimum Prerequisite on Composite

Air Force

Course	Sample Size White (%)	Black (%)	Total	Prerequisite
Composite: Administrative (AIA)				
70230A	328 (65)	180 (35)	508	AIA=35
70230B	1581 (64)	880 (36)	2461	AIA=35
70230C	594 (65)	319 (35)	913	AIA=35
73230	874 (71)	358 (29)	1232	AIA=50
64530	1429 (73)	541 (27)	1970	AIA=50 OR AIG=45
Composite: Electronic (AIE)				
42330	701 (82)	153 (18)	854	AIE=40
42334	558 (79)	146 (21)	704	AIE=35 OR AIM=40
42335	1357 (83)	278 (17)	1635	AIE=30 AND AIM=35
46130	1176 (87)	177 (13)	1353	AIE=45 OR AIM=45
Composite: General (AIG)				
63130	1394 (83)	281 (17)	1676	AIG=40 AND AIM=35
27230	765 (82)	163 (18)	928	AIG=45
62230	555 (73)	201 (27)	756	AIG=30
64531	635 (69)	281 (31)	916	AIG=30
29130	538 (71)	215 (29)	753	AIG=45
90230	1016 (78)	284 (22)	1300	AIG=45
90630	298 (73)	109 (27)	407	AIG=45
98130	331 (74)	115 (26)	446	AIG=45
81132	2759 (80)	677 (20)	3436	AIG=35
Composite: Mechanical (AIM)				
42331	399 (76)	126 (24)	525	AIM=30
42333	512 (84)	101 (16)	613	AIM=35
42632	1656 (89)	210 (11)	1866	AIM=30
43131	2699 (90)	301 (10)	3000	AIM=35
43132	2695 (89)	361 (11)	3020	AIM=35

Table 2B

Training Courses, Sample Sizes, and Minimum Prerequisite on Composite

Marine Corps

Course	Sample Size White (%)	Black (%)	Total	Prerequisite
Composite: Clerical				
0151	445 (73)	168 (27)	613	CL=100,110*
2542	217 (68)	103 (32)	320	CL=110
3043	549 (87)	85 (13)	634	CL=110
Composite: Electronic (EL)				
2531	682 (79)	181 (21)	863	EL=90,100
Composite: General-Technical (GT)				
3371	391 (81)	91 (19)	482	GT=90,100*

* current,proposed

Table 3A

Sufficient Statistics

Air Force

Administrative		White			Black		
Course	Variable	Mean	SD	r	Mean	SD	r
70230A	FCG	83.8	6.9		80.9	6.1	
	VE	52.3	5.2	.38	49.9	5.0	.29
	NO	55.9	5.1	.09	54.6	6.1	-.02
	CS	55.1	6.2	.01	54.1	6.2	-.01
	AIA	65.3	15.9	.25	57.7	15.7	.13
70230B	FCG	87.0	6.7		85.0	6.6	
	VE	52.6	5.0	.36	49.4	5.2	.18
	NO	55.0	5.6	.12	54.3	5.6	-.02
	CS	54.6	6.4	.13	52.5	6.7	-.02
	AIA	63.3	17.7	.29	54.2	16.2	.06
70230C	FCG	85.7	6.7		83.3	6.3	
	VE	52.4	5.2	.37	49.4	5.0	.29
	NO	54.9	5.6	.06	54.9	5.4	-.02
	CS	54.0	6.5	.11	52.5	6.5	.04
	AIA	62.1	17.3	.27	54.9	15.5	.17
73230	FCG	87.3	6.1		84.8	5.7	
	VE	54.1	4.9	.41	50.9	5.0	.31
	NO	57.0	4.7	.14	56.2	4.6	.01
	CS	56.4	6.0	.16	55.0	5.8	.04
	AIA	71.8	14.8	.36	63.3	13.3	.22
64530	FCG	77.6	8.1		75.8	7.7	
	VE	53.2	4.9	.36	50.5	5.3	.32
	NO	56.1	5.4	.10	55.6	5.5	-.01
	CS	55.1	7.0	.10	54.3	6.7	-.08
	AIA	66.9	17.6	.26	60.7	15.7	.11

cont. Table 3A

Electrical		White			Black		
Course	Variable	Mean	SD	r	Mean	SD	r
42330	FCG	86.1	6.2		83.2	5.9	
	AR	56.7	6.4	.41	51.7	6.0	.24
	MK	55.2	7.2	.46	52.3	6.4	.32
	EI	57.3	7.1	.36	52.4	7.8	.35
	GS	55.3	6.9	.37	49.4	6.7	.28
	AIE	71.2	16.5	.53	55.4	15.5	.45
42334	FCG	82.1	6.7		79.0	5.6	
	AR	52.4	6.5	.34	48.7	5.4	.09
	MK	49.0	6.5	.30	48.2	5.4	.12
	EI	54.3	7.0	.46	50.0	6.4	.33
	GS	52.3	6.9	.38	48.1	6.8	.14
	AIE	57.4	16.5	.52	45.7	11.3	.33
42335	FCG	85.4	5.2		84.3	4.8	
	AR	52.1	6.5	.29	48.3	5.4	.15
	MK	49.5	6.5	.26	48.1	5.9	.18
	EI	54.2	6.8	.31	51.4	6.7	.11
	GS	52.3	6.4	.28	49.5	6.0	.01
	AIE	57.5	15.4	.42	48.2	12.0	.19
46130	FCG	85.8	4.8		83.7	4.4	
	AR	53.8	6.8	.41	51.0	5.7	.26
	MK	51.2	7.2	.40	50.5	5.8	.22
	EI	56.0	6.3	.32	51.5	5.4	.07
	GS	54.1	6.3	.35	50.4	6.1	.03
	AIE	63.4	15.8	.52	53.4	10.3	.28

cont. Table 3A

General Course	Variable	White Mean	White SD	White r	Black Mean	Black SD	Black r
63130	FCG	85.0	6.0		82.3	5.8	
	VE	52.7	5.1	.35	50.5	5.5	.17
	AR	54.3	6.4	.33	49.4	5.9	.31
	AIG	60.4	17.9	.42	47.0	15.4	.33
27230	FCG	83.6	5.8		80.8	5.3	
	VE	55.0	4.2	.35	53.2	3.8	.15
	AR	57.1	5.8	.44	54.2	5.4	.38
	AIG	70.0	16.2	.50	60.7	13.8	.38
62230	FCG	82.5	7.6		79.9	7.0	
	VE	51.6	5.2	.39	48.9	5.5	.32
	AR	51.9	6.6	.29	49.2	6.0	.20
	AIG	53.7	17.4	.43	43.7	14.1	.39
64530	FCG	77.6	8.1		75.8	7.7	
	VE	53.2	4.9	.36	50.6	5.3	.32
	AR	54.8	6.8	.34	50.1	5.9	.25
	AIG	62.3	18.2	.44	48.3	15.1	.38
64531	FCG	82.5	7.5		81.2	7.1	
	VE	51.5	5.4	.32	48.6	5.0	.16
	AR	52.4	6.9	.38	49.0	5.6	.16
	AIG	54.4	18.5	.45	42.6	12.6	.24
29130	FCG	85.9	6.7		83.6	7.1	
	VE	54.8	4.2	.32	52.8	4.1	.22
	AR	55.7	5.6	.32	52.4	4.8	.12
	AIG	66.6	14.9	.42	56.1	10.6	.28
90230	FCG	83.4	5.4		80.2	5.0	
	VE	54.8	4.1	.50	53.2	3.9	.38
	AR	55.7	5.7	.29	52.7	5.0	.14
	AIG	66.9	15.2	.49	57.5	11.7	.38
90630	FCG	80.8	6.2		80.4	6.6	
	VE	54.4	4.3	.37	53.0	3.8	.08
	AR	55.4	5.4	.30	51.5	4.4	.24
	AIG	65.3	14.2	.44	54.7	10.0	.27
98130	FCG	86.3	5.9		84.4	5.9	
	VE	54.5	4.4	.38	52.9	3.4	.16
	AR	56.0	5.8	.23	53.3	4.8	.15
	AIG	66.8	15.2	.40	58.0	11.9	.21
81132	FCG	77.8	6.7		74.5	6.6	
	VE	53.6	4.8	.42	50.1	5.2	.32
	AR	54.6	6.4	.31	50.4	5.5	.11
	AIG	62.4	17.9	.44	47.7	14.1	.30

cont. Table 3A

Mechanical		White			Black		
Course	Variable	Mean	SD	r	Mean	SD	r
42331	FCG	82.4	5.7		81.2	4.7	
	MC	54.4	6.7	.24	50.8	5.9	.07
	GS	51.8	6.9	.31	48.5	6.4	.22
	AS	57.2	6.9	.28	51.1	5.4	.08
	AIM	67.8	17.0	.36	51.9	13.5	.17
42333	FCG	84.2	6.1		81.7	5.8	
	MC	54.8	7.4	.41	50.7	6.6	-.03
	GS	51.9	6.6	.32	47.8	6.0	-.10
	AS	57.2	6.8	.36	50.8	5.8	.09
	AIM	68.2	17.7	.44	50.6	13.2	.01
42334	FCG	82.1	6.7		79.0	5.7	
	MC	55.0	7.8	.39	48.7	6.9	.24
	GS	52.3	6.9	.38	48.1	6.8	.14
	AS	57.8	7.9	.38	48.4	6.5	.18
	AIM	69.3	20.1	.45	44.9	18.1	.24
42335	FCG	85.4	5.2		84.3	4.8	
	MC	55.3	6.9	.36	51.1	5.6	.22
	GS	52.3	6.4	.28	49.5	6.0	.01
	AS	57.9	7.0	.37	51.2	6.0	.12
	AIM	70.2	16.9	.43	53.4	14.0	.17
42632	FCG	85.3	6.8		81.7	5.7	
	MC	56.9	7.1	.39	51.3	6.2	.26
	GS	53.5	6.5	.33	49.8	6.3	.19
	AS	59.6	6.8	.38	53.1	5.9	.29
	AIM	74.9	16.6	.45	57.1	15.3	.35
63130	FCG	85.0	6.0		82.3	5.8	
	MC	55.5	7.2	.29	50.2	6.0	.20
	GS	53.6	6.6	.32	49.4	7.0	.11
	AS	57.7	6.7	.34	51.9	5.8	.18
	AIM	71.0	16.9	.41	53.8	13.3	.27
46130	FCG	85.8	4.8		83.7	4.4	
	MC	57.6	6.4	.31	50.2	7.0	.21
	GS	54.2	6.3	.35	50.4	6.1	.03
	AS	60.1	6.1	.30	50.6	6.9	.11
	AIM	77.1	13.9	.40	52.2	17.9	.16
43131	FCG	80.8	7.9		76.3	7.5	
	MC	57.4	6.5	.32	53.9	5.7	.14
	GS	53.6	6.4	.37	50.7	6.1	.20
	AS	60.5	5.2	.31	55.7	5.0	.09
	AIM	77.3	12.4	.44	65.2	10.4	.22
43132	FCG	81.3	7.9		77.8	7.4	
	MC	57.2	6.6	.36	53.0	5.9	.17
	GS	53.5	6.5	.40	50.7	6.1	.15
	AS	60.2	5.5	.33	55.8	5.2	.11
	AIM	76.6	12.9	.48	64.4	11.4	.21

Table 3B

Sufficient Statistics

Marine Corps

		White			Black		
Course	Variable	Mean	SD	r	Mean	SD	r
Clerical Specialty							
0151	FCG	91.2	5.9		89.7	6.7	
	VE	52.8	5.7	.31	49.4	6.3	.31
	NO	54.4	7.5	.21	51.8	9.5	.23
	CS	53.9	9.2	.21	50.7	9.7	.30
	CL	107.3	15.6	.29	99.3	17.0	.35
2542	FCG	77.8	14.1		78.0	12.6	
	VE	51.7	6.6	.41	47.8	7.1	.36
	NO	56.0	6.8	.11	55.8	5.9	.14
	CS	55.1	9.1	-.03	54.8	10.1	-.21
	CL	108.7	13.2	.21	104.8	12.4	.09
3043	FCG	88.0	7.2		84.9	7.3	
	VE	55.0	5.0	.41	50.2	6.5	.42
	NO	58.2	6.1	.32	56.3	7.4	.29
	CS	58.1	7.9	.33	56.9	10.8	.27
	CL	116.8	13.3	.45	109.7	16.8	.42
Electronics Specialty							
2531	FCG	87.9	10.1		87.0	10.2	
	AR	51.4	6.5	.07	48.2	5.5	.07
	MK	49.8	6.6	.20	48.9	6.3	.15
	EI	54.0	6.9	.14	49.3	7.6	.26
	GS	52.5	6.8	.15	48.8	7.9	.23
	EL	103.9	10.4	.20	96.8	11.2	.27
General-Technical Specialty							
3371	FCG	87.9	4.1		85.3	4.4	
	VE	52.2	5.8	.22	48.7	6.1	.38
	AR	53.9	7.2	.22	50.0	6.4	.15
	GT	106.6	12.2	.26	98.2	11.4	.31

Table 4A

Means of Marginal Posterior Distributions
for Single Predictor Regression Analyses

Air Force

Administrative Specialty

Predictor	Combined bo	b1	RMSE	White bo	b1	RMSE	Black bo	b1	RMSE
Course: 70230A									
AIA	76.35	.10	6.57	76.72	.11	6.69	78.02	.05	6.01
VE	57.07	.50	6.26	57.43	.50	6.39	62.66	.36	5.85
NO	77.89	.09	6.76	76.89	.12	6.88	81.89	-.02	6.09
CS	81.52	.02	6.77	83.18	.01	6.80	81.28	-.01	6.02
Course: 70230B									
AIA	80.84	.09	6.54	80.05	.11	6.41	83.68	.02	6.59
VE	65.02	.41	6.38	61.63	.48	6.25	73.46	.23	6.50
NO	81.46	.09	6.72	79.10	.14	6.65	86.28	-.02	6.60
CS	81.15	.10	6.71	79.57	.14	6.65	86.03	-.02	6.60
Course: 70230C									
AIA	78.73	.10	6.39	79.21	.10	6.45	79.51	.07	6.22
VE	61.33	.46	6.17	60.72	.48	6.23	65.25	.37	6.04
NO	82.42	.04	6.62	81.76	.07	6.60	84.58	-.02	6.25
CS	79.25	.10	6.59	79.58	.11	6.61	81.26	.04	6.29
Course: 73230									
AIA	76.41	.15	5.71	76.65	.15	5.69	78.83	.09	5.57
VE	60.36	.49	5.57	59.69	.51	5.56	66.81	.35	5.43
NO	77.91	.15	6.07	76.94	.18	5.95	84.10	.01	5.69
CS	78.53	.14	6.05	78.13	.16	6.02	82.64	.04	5.65
Course: 64530									
AIA	69.86	.11	7.82	69.59	.12	7.82	72.53	.05	7.60
VE	47.63	.56	7.52	45.94	.60	7.56	52.32	.46	7.30
NO	71.00	.11	8.03	69.13	.15	8.01	76.58	-.01	7.65
CS	73.47	.07	8.04	71.22	.12	8.01	80.79	-.09	7.64

bo = intercept, b1 = slope, RMSE = root mean-square error

cont. Table 4A

Electronics Specialty

Predictor	Combined bo	Combined b1	Combined RMSE	White bo	White b1	White RMSE	Black bo	Black b1	Black RMSE
Course: 42330									
AIE	72.39	.19	5.23	71.92	.20	5.26	73.71	.17	5.29
AR	64.14	.38	5.67	63.58	.40	5.66	71.00	.24	5.75
MK	64.13	.39	5.54	64.23	.40	5.51	67.77	.29	5.61
EI	67.44	.32	5.73	68.09	.31	5.79	69.33	.26	5.55
GS	67.37	.33	5.72	67.71	.33	5.76	71.02	.25	5.68
Course: 42334									
AIE	69.88	.21	5.68	69.98	.21	5.73	71.53	.16	5.31
AR	64.10	.34	6.27	63.74	.35	6.31	74.45	.09	5.58
MK	67.02	.30	6.37	66.95	.31	6.40	73.00	.12	5.57
EI	58.15	.44	5.86	58.19	.44	5.95	64.56	.29	5.31
GS	63.86	.34	6.18	62.80	.37	6.20	73.45	.12	5.56
Course: 42335									
AIE	77.69	.13	4.77	77.25	.14	4.72	80.64	.08	4.72
AR	73.59	.23	4.98	73.14	.24	5.02	77.99	.13	4.75
MK	74.99	.21	5.02	75.10	.21	5.02	77.26	.15	4.73
EI	73.43	.22	4.97	72.55	.24	4.96	80.25	.08	4.78
GS	74.80	.20	5.03	73.50	.23	4.99	83.90	.01	4.79
Course: 46130									
AIE	75.76	.16	4.14	75.78	.16	4.10	77.31	.12	4.24
AR	69.99	.29	4.38	70.23	.29	4.38	73.46	.20	4.26
MK	72.29	.26	4.45	72.15	.27	4.40	75.27	.17	4.30
EI	72.42	.24	4.56	72.15	.24	4.55	80.76	.06	4.39
GS	72.34	.25	4.54	71.37	.27	4.50	82.61	.02	4.41

cont. Table 4A

General Speciality

Predictor	Combined bo	Combined b1	Combined RMSE	White bo	White b1	White RMSE	Black bo	Black b1	Black RMSE
Course: 63130									
AIG	76.13	.14	5.49	76.50	.14	5.45	76.46	.12	5.48
VE	64.10	.39	5.72	63.30	.41	5.62	73.25	.18	5.73
AR	67.03	.34	5.69	68.20	.31	5.67	67.25	.30	5.52
Course: 27230									
AIG	70.91	.18	5.01	71.07	.18	5.03	71.94	.15	4.92
VE	57.49	.47	5.44	57.02	.48	5.44	69.67	.21	5.26
AR	58.13	.44	5.17	58.48	.44	5.21	60.59	.37	4.92
Course: 62230									
AIG	72.01	.19	6.75	71.41	.19	6.87	71.44	.19	6.46
VE	54.11	.54	6.91	53.09	.57	7.01	59.98	.41	6.65
AR	64.82	.33	7.19	65.17	.33	7.28	68.42	.23	6.88
Course: 64530									
AIG	66.21	.19	7.27	65.40	.20	7.28	66.44	.19	7.13
VE	47.63	.56	7.52	45.94	.60	7.56	52.28	.46	7.30
AR	56.21	.39	7.59	55.41	.40	7.62	59.45	.33	7.46
Course: 64531									
AIG	73.60	.17	6.79	72.58	.18	6.70	75.44	.14	6.91
VE	62.53	.39	7.11	59.61	.44	7.11	70.16	.23	7.02
AR	63.42	.36	7.00	60.86	.41	6.94	71.26	.20	7.02
Course: 29130									
AIG	73.13	.19	6.29	73.32	.19	6.09	73.08	.19	6.83
VE	57.67	.51	6.54	57.93	.51	6.35	63.48	.38	6.94
AR	65.52	.36	6.58	64.57	.38	6.35	74.30	.18	7.07
Course: 90230									
AIG	70.92	.18	4.71	71.75	.17	4.71	70.86	.16	4.63
VE	47.08	.65	4.74	47.31	.66	4.68	54.28	.49	4.63
AR	66.64	.29	5.19	68.10	.27	5.17	72.82	.14	4.96
Course: 90630									
AIG	69.86	.17	5.81	68.26	.19	5.58	70.65	.18	6.39
VE	56.55	.45	6.01	51.78	.53	5.77	73.04	.14	6.55
AR	63.47	.32	6.05	61.72	.34	5.92	61.86	.36	6.44
Course: 98130									
AIG	76.08	.15	5.52	75.93	.16	5.41	78.36	.10	5.79
VE	59.21	.49	5.59	58.53	.51	5.47	69.71	.28	5.85
AR	72.19	.25	5.80	73.20	.23	5.75	74.57	.18	5.86
Course: 81132									
AIG	67.08	.17	6.09	67.52	.16	6.02	67.80	.14	6.30
VE	46.67	.58	6.16	46.38	.59	6.08	54.15	.41	6.26
AR	59.28	.33	6.48	60.08	.32	6.37	67.85	.13	6.56

cont. Table 4A

Mechanical Speciality									
	Combined			White			Black		
Predictor	bo	bl	RMSE	bo	bl	RMSE	bo	bl	RMSE
Course: 42331									
AIM	75.38	.11	5.15	74.22	.12	5.33	78.13	.06	4.65
MC	72.38	.18	5.34	71.29	.20	5.54	78.37	.06	4.69
GS	69.92	.24	5.22	69.13	.26	5.43	73.36	.16	4.61
AS	70.72	.20	5.28	69.17	.23	5.48	77.64	.07	4.69
Course: 42333									
AIM	74.70	.14	5.56	73.86	.15	5.48	81.48	.01	5.79
MC	67.51	.30	5.69	65.68	.34	5.57	83.04	-.03	5.79
GS	70.67	.26	5.87	68.85	.30	5.87	86.32	-.10	5.87
AS	66.76	.30	5.72	65.73	.32	5.72	77.13	.09	5.72
Course: 42334									
AIM	72.81	.13	5.93	71.70	.15	5.99	75.61	.08	5.55
MC	63.62	.33	6.07	63.67	.33	6.18	69.34	.20	5.55
GS	63.86	.34	6.18	62.80	.37	6.20	73.36	.12	5.66
AS	64.43	.31	6.10	63.47	.32	6.20	71.36	.16	5.63
Course: 42335									
AIM	77.33	.12	4.76	76.11	.13	4.70	81.19	.06	4.74
MC	70.97	.26	4.87	70.40	.27	4.85	74.66	.19	4.69
GS	74.80	.20	5.03	73.50	.23	4.99	83.90	.01	4.79
AS	71.33	.24	4.88	69.49	.27	4.83	79.38	.10	4.77
Course: 42632									
AIM	71.65	.18	5.98	71.49	.18	6.07	74.25	.13	5.35
MC	63.79	.38	6.20	64.05	.37	6.26	69.44	.24	5.52
GS	66.47	.35	6.36	66.83	.35	6.42	73.14	.17	5.61
AS	62.18	.39	6.21	62.65	.38	6.29	66.82	.28	5.47
Course: 63130									
AIM	74.66	.14	5.53	74.67	.15	5.47	75.97	.12	5.59
MC	70.35	.26	5.79	71.59	.24	5.74	72.59	.19	5.69
GS	69.84	.28	5.78	69.41	.29	5.69	77.80	.09	5.77
AS	67.24	.30	5.71	67.43	.30	5.65	72.96	.18	5.72
Course: 46130									
AIM	77.43	.11	4.44	75.15	.14	4.40	81.65	.04	4.36
MC	72.92	.22	4.55	72.41	.23	4.56	77.07	.13	4.31
GS	72.34	.25	4.54	71.35	.27	4.50	82.61	.02	4.39
AS	73.10	.21	4.57	71.61	.24	4.58	80.15	.07	4.38
Course: 43131									
AIM	59.01	.28	7.12	59.13	.28	7.10	65.96	.16	7.33
MC	57.39	.40	7.52	58.48	.39	7.49	66.37	.18	7.43
GS	56.00	.46	7.41	56.32	.46	7.34	63.83	.25	7.36
AS	52.26	.47	7.56	52.31	.47	7.51	68.78	.13	7.48
Course: 43132									
AIM	59.88	.28	7.01	58.75	.29	6.93	69.02	.14	7.25
MC	56.78	.43	7.41	56.65	.43	7.37	66.50	.21	7.30
GS	55.94	.47	7.31	55.29	.49	7.24	68.57	.18	7.33
AS	53.37	.46	7.48	52.77	.47	7.46	69.07	.16	7.36

Table 4B

Means of Marginal Posterior Distributions
for Single Predictor Regression Analyses

Marine Corps

Predictor	Combined bo	b1	RMSE	White bo	b1	RMSE	Black bo	b1	RMSE
Clerical Specialty									
Course: 0151									
CL	77.97	.12	5.80	79.36	.11	5.61	76.04	.13	6.29
VE	73.90	.32	5.80	74.78	.31	5.59	73.18	.33	6.37
NO	81.38	.17	5.97	82.05	.17	5.73	81.15	.17	6.53
CS	82.23	.16	5.94	84.09	.13	5.74	79.13	.21	6.40
Course: 2542									
CL	58.41	.18	13.46	53.46	.22	13.80	68.10	.09	12.57
VE	40.51	.74	12.64	31.72	.89	12.88	47.56	.64	11.84
NO	64.43	.24	13.57	65.31	.22	14.00	61.86	.29	12.55
CS	84.83	-.13	13.61	80.66	-.05	14.00	91.99	-.26	12.42
Course: 3043									
CL	60.34	.24	6.47	59.99	.24	6.42	64.64	.18	6.70
VE	56.93	.56	6.57	56.22	.58	6.55	61.15	.47	6.72
NO	65.74	.38	6.86	65.83	.38	6.78	68.70	.29	7.08
CS	71.33	.28	6.87	70.59	.30	6.76	74.26	.19	7.11
Electronics Specialty									
Course: 2531									
EL	67.40	.20	9.85	68.08	.19	9.87	63.38	.24	9.81
AR	81.96	.11	10.07	82.74	.10	10.05	80.55	.13	10.15
MK	73.07	.30	9.91	72.73	.31	9.87	75.20	.24	10.06
EI	75.52	.23	9.95	77.26	.20	9.98	71.13	.34	9.84
GS	75.22	.24	9.94	76.20	.22	9.96	72.79	.29	9.91
General-Technical Specialty									
Course: 3371									
GT	76.17	.11	4.05	78.53	.09	3.96	73.95	.12	4.17
VE	76.52	.21	4.07	79.55	.16	4.00	72.05	.27	4.04
AR	79.72	.14	4.14	81.18	.12	4.00	80.32	.10	4.32

bo = intercept, b1 = slope, RMSE = root mean-square error

Table 5A

Johnson-Neyman Regions of Rejection

Air Force

Administrative Speciality

Training Course	Predictor	Xo	Region of Rejection	Proportion Affected Total	Black
70230A	AIA	22	AIA > 46	.81	.68
	VE	37	VE > 47	.83	.59
	NO	36	NO > 47	.90	.85
	CS	-95	40 < CS < 74	.99	1.00
70230B	AIA	40	AIA < 33 OR AIA > 49	.70	.68
	VE	47	VE < 45 OR VE > 49	.74	.69
	NO	45	NO < 31 OR NO > 47	.88	.83
	CS	40	CS < 31 OR CS > 46	.89	.84
70230C	AIA	10	AIA > 39	.84	.78
	VE	41	VE > 48	.66	.51
	NO	31	NO > 45	.91	.94
	CS	24	CS > 42	.95	.94
73230	AIA	36	AIA > 55	.76	.63
	VE	45	VE < 26 OR VE > 50	.71	.55
	NO	42	NO > 49	.89	.88
	CS	38	CS > 46	.96	.90
64530	AIA	42	AIA > 55	.67	.57
	VE	46	VE > 55	.21	.14
	NO	47	NO > 51	.78	.79
	CS	46	CS < 37 OR CS > 50	.71	.72

Xo represents the point on the abscissa where the regression lines intersect

cont. Table 5A

Electronics Speciality

Training Course	Predictor	Xo	Region of Rejection	Proportion Affected Total	Black
42330	AIE	60	No Region	----	----
	AR	46	AR > 52	.65	.37
	MK	32	MK > 46	.80	.72
	EI	25	47 < EI < 74	.80	.61
	GS	41	49 < GS < 73	.68	.40
42334	AIE	31	52 < AIE < 61	.07	.08
	AR	41	AR > 46	.70	.55
	MK	32	MK > 41	.79	.79
	EI	42	EI > 48	.68	.51
	GS	43	GS < 32 OR GS > 46	.63	.44
42335	AIE	57	AIE < 43 OR AIE > 64	.41	.43
	AR	44	No Region	----	----
	MK	36	45 < MK < 75	.72	.68
	EI	48	EI < 43 OR EI > 52	.52	.31
	GS	47	GS < 44 OR GS > 50	.64	.63
46130	AIE	38	54 < AIE < 90	.78	.72
	AR	36	AR > 46	.83	.84
	MK	31	MK > 42	.85	.89
	EI	48	EI < 36 OR EI > 50	.81	.44
	GS	45	GS < 41 OR GS > 49	.68	.51

cont. Table 5A

General Speciality					
Training Course	Predictor	Xo	Region of Rejection	Proportion Affected Total	Black
63130	AIG	- 2	40 < AIG < 82	.72	.59
	VE	43	VE < 34 OR VE > 46	.81	.74
	AR	-95	40 < AR < 61	.83	.90
27230	AIG	29	AIG > 53	.76	.68
	VE	47	VE < 26 OR VE > 50	.88	.80
	AR	30	48 < AR < 76	.93	.89
62230	AIG	128	No Region	----	----
	VE	43	VE > 48	.62	.54
	AR	32	45 < AR < 78	.85	.81
64530	AIG	104	32 < AIG < 68	.66	.79
	VE	45	VE > 54	.36	.22
	AR	57	No Region	----	----
64531	AIG	71	AIG < 43	.45	.65
	VE	50	VE < 41 OR VE > 54	.39	.27
	AR	50	AR < 44 OR AR > 55	.43	.33
29130	AIG	-10	No Region	----	----
	VE	42	51 < VE < 69	.81	.73
	AR	49	AR > 52	.67	.49
90230	AIG	-89	AIG > 32	1.00	1.00
	VE	41	VE > 47	.94	.95
	AR	36	AR > 44	.98	.98
90630	AIG	239	42 < AIG < 66	.65	.84
	VE	54	VE < 50 OR VE 59	.36	.30
	AR	-7	No Region	----	----
98130	AIG	41	No Region	----	----
	VE	48	53 < VE < 77	.64	.56
	AR	27	51 < AR < 59	.48	.42
81132	AIG	14	AIG > 36	.90	.79
	VE	43	VE < 36 OR VE > 46	.88	.75
	AR	41	AR < 32 OR AR > 44	.94	.84

con. Table 5A

Mechanical Specialty

Training Course	Predictor	Xo	Region of Rejection	Proportion Affected White	Black
42331	AIM	65	AIM < 46	.22	.45
	MC	51	MC > 55	.46	.32
	GS	42	No Region	----	----
	AS	53	AS < 30	.00	.01
42333	AIM	54	AIM < 43 OR AIM > 60	.75	.62
	MC	47	MC < 43 OR MC > 50	.30	.24
	GS	44	GS < 40 OR GS > 47	.76	.60
	AS	50	AS < 37 OR AS > 54	.59	.26
42334	AIM	56	AIM < 36 OR AIM > 73	.52	.42
	MC	44	MC > 49	.72	.52
	GS	42	GS < 32 OR GS > 46	.73	.57
	AS	49	AS < 30 OR AS > 56	.52	.13
42335	AIM	72	AIM < 61 OR AIM > 84	.57	.76
	MC	53	No Region	----	----
	GS	47	GS < 44 OR GS > 50	.75	.63
	AS	58	AS < 52 OR AS > 60	.63	.65
42632	AIM	55	AIM > 67	.67	.29
	MC	41	MC > 47	.81	.77
	GS	35	GS > 43	.93	.82
	AS	42	AS > 51	.86	.66
63130	AIM	43	No Region	----	----
	MC	20	43 < MC < 77	.94	.92
	GS	42	GS < 34 OR GS > 46	.88	.77
	AS	46	AS > 50	.79	.57
46130	AIM	65	AIM < 59 OR AIM > 75	.69	.70
	MC	47	MC > 53	.65	.40
	GS	45	GS < 41 OR GS > 49	.77	.65
	AS	50	AS < 46 OR AS > 56	.78	.48
43131	AIM	57	AIM < 41 OR AIM > 63	.81	.53
	MC	38	MC > 45	.96	.94
	GS	36	GS > 42	.97	.94
	AS	48	AS < 43 OR AS > 52	.92	.77
43132	AIM	68	AIM < 61 OR AIM > 70	.83	.75
	MC	45	MC < 35 OR MC > 49	.87	.74
	GS	43	GS < 39 OR GS > 46	.84	.76
	AS	53	AS < 47 OR AS > 54	.83	.67

Table 5B

Johnson-Neyman Regions of Rejection

Marine Corps

Training Course	Predictor	Xo	Region of Rejection	Proportion Affected Total	Black
Clerical Specialty					
0151	CL	166	No Region	----	----
	VE	80	No Region	----	----
	NO	-90	47 < NO < 58	.47	.43
	CS	62	CS < 53	.49	.65
2542	CL	112	No Region	----	----
	VE	63	25 < VE < 52	.54	.71
	NO	49	No Region	----	----
	CS	54	No Region	----	----
3043	CL	78	CL > 109	.76	.61
	VE	45	No Region	----	----
	NO	32	NO > 50	.85	.74
	CS	33	CS > 48	.84	.63
Electronics Specialty					
2531	EL	94	No Region	----	----
	AR	73	No Region	----	----
	MK	35	No Region	----	----
	EI	44	No Region	----	----
	GS	49	No Region	----	----
General-Technical Specialty					
3371	GT	153	50 < GT < 115	.84	.96
	VE	68	VE < 56	.75	.95
	AR	-43	37 < AR < 71	.98	.96

Xo represents the point on the abscissa where the regression lines intersect

Table 6

Comparison of White and Black Predictions
At the Cut-off Level on Appropriate ASVAB
Selector Composite

Air Force

Course	(Composite = Cut-Off)	Mean*	90% Credibility Interval
42335	(AIE = 30)	-1.59	-2.57 to -0.61
63130	(AIG = 40)	.84	.15 to 1.53
64530	(AIG = 45)	-.59	-1.13 to -0.04
64531	(AIG = 30)	-1.66	-2.83 to -0.49
90230	(AIG = 45)	1.34	.51 to 2.17
90630	(AIG = 45)	-1.94	-3.54 to -0.34
42331	(AIM = 30)	-2.11	-3.75 to -0.47
42333	(AIM = 35)	-2.72	-4.78 to -0.66
42335	(AIM = 35)	-2.63	-3.48 to -1.78
46130	(AIM = 45)	-2.00	-2.74 to -1.26
43131	(AIM = 35)	-2.63	-4.64 to -0.62
43132	(AIM = 35)	-5.02	-7.40 to -2.64

Marine Corps

3043	(CL = 110)	1.95	.98 to 2.92
3371	(GT = 90)	1.88	.45 to 3.31
	(GT = 100)	1.58	.30 to 2.86

* White - Black

Table 7A

Regression Models for Multiple Predictors

Air Force

Administrative Specialty

Course		70230A	70230B	70230C	73230	64530
INTERCEPT		58.33	73.43	56.77	51.86	43.05
VE		.38	.23	.39	.42	.51
NO		.06	.01	.06	.11	.15
CS		.00	-.01	.08	.11	-.02
RACE		-12.81	-23.58	-6.78	-11.75	-10.35
RACE*VE		.14	.26	.09	.12	.10
RACE*NO		.11	.09	.02	.08	.00
RACE*CS		.02	.11	.04	.03	.10
RMSE	W	6.36	6.14	6.13	5.43	7.50
	B	5.85	6.54	6.03	5.40	7.32
RSQ	W	.16	.16	.15	.22	.15
	B	.09	.03	.09	.12	.11

Electronics Specialty

Course		42330	42334	42335	46130
INTERCEPT		53.15	52.04	70.55	63.25
AR		.08	.04	.10	.17
MK		.21	.15	.11	.10
EI		.22	.28	.09	.06
GS		.07	.07	-.02	.06
RACE		-3.61	-8.31	-10.96	-5.93
RACE*AR		.04	.11	.04	-.02
RACE*MK		.03	-.05	-.03	.02
RACE*EI		-.03	.03	.08	.07
RACE*GS		.03	.09	.12	.06
RMSE	W	5.17	5.67	4.75	4.11
	B	5.26	5.33	4.72	4.24
RSQ	W	.30	.29	.18	.27
	B	.22	.14	.05	.10

Variables preceded by RACE represent interaction terms.
RMSE = Root Mean Squared Error
RSQ = Squared Multiple Correlation Coefficient

cont. Table 7A

General Specialty Course		63130	27230	62230	64530	64531
INTERCEPT		60.41	53.08	45.69	38.99	57.44
VE		.15	.15	.44	.44	.26
AR		.29	.37	.26	.29	.23
RACE		-5.17	-8.98	-1.50	-3.76	-10.75
RACE*VE		.18	.19	.06	.03	.08
RACE*AR		-.06	.00	-.02	.03	.12
RMSE	W	5.48	5.00	6.81	7.29	6.74
	B	5.48	4.94	6.46	7.15	6.91
RSQ	W	.18	.25	.19	.19	.20
	B	.12	.16	.16	.15	.06

General Specialty Course		29130	90230	90630	98130	81132
INTERCEPT		42.96	40.41	44.30	61.00	47.30
VE		.49	.54	.27	.26	.40
AR		.29	.21	.42	.18	.14
RACE		.07	-.97	-8.63	-12.69	-7.53
RACE*VE		-.04	.06	.24	.23	.10
RACE*AR		.05	-.01	-.11	.02	.07
RMSE	W	6.09	4.52	5.49	5.34	5.97
	B	6.78	4.54	6.42	5.84	6.18
RSQ	W	.18	.29	.21	.19	.21
	B	.08	.19	.08	.04	.11

cont. Table 7A

Mechanical Specialty						
Course		42331	42333	42334	42335	42632
INTERCEPT		69.97	83.99	64.81	72.36	57.51
MC		.03	-.04	.16	.17	.15
GS		.15	-.09	.06	.00	.12
AS		.05	.09	.07	.06	.20
RACE		-9.86	-27.83	-12.44	-11.62	-7.11
RACE*MC		.03	.26	.00	-.03	.05
RACE*GS		.04	.24	.16	.12	.08
RACE*AS		.12	.06	.09	.12	.02
RMSE	W	5.25	5.41	5.91	4.70	5.96
	B	4.68	5.80	5.52	4.72	5.40
RSQ	W	.14	.22	.23	.20	.23
	B	.05	.02	.07	.05	.13

Mechanical Specialty					
Course		63130	46130	43131	43132
INTERCEPT		59.33	76.77	46.67	51.60
MC		.19	.13	.14	.18
GS		.08	-.01	.24	.16
AS		.18	.03	.18	.15
RACE		-1.22	-17.78	-14.21	-20.96
RACE*MC		-.08	-.01	.07	.05
RACE*GS		.11	.21	.10	.20
RACE*AS		.01	.13	.12	.15
RMSE	W	5.49	4.31	6.97	6.81
	B	5.59	4.34	7.29	7.24
RSQ	W	.17	.20	.22	.26
	B	.08	.05	.06	.06

Table 7B

Regression Models for Multiple Predictors

Marine Corps

Clerical Specialty

Course		0151	2542	3043
INTERCEPT		66.99	44.22	50.76
VE		.28	.52	.42
NO		.00	.37	.15
CS		.17	-.21	.08
RACE		3.15	-25.60	-7.24
RACE*VE		-.02	.37	.04
RACE*NO		.09	-.08	.01
RACE*CS		-.13	.16	.09
RMSE	W	5.52	12.82	6.27
	B	6.19	11.72	6.56
RSQ	W	.12	.19	.24
	B	.16	.16	.23

Electronics Specialty

Course		2531
INTERCEPT		62.86
AR		-.10
MK		.16
EI		.26
GS		.17
RACE		4.69
RACE*AR		-.01
RACE*MK		.15
RACE*EI		-.15
RACE*GS		-.08
RMSE	W	9.81
	B	9.79
RSQ	W	.06
	B	.09

General-Technical Specialty

Course		3371
INTERCEPT		71.49
VE		.27
AR		.02
RACE		5.30
RACE*VE		-.15
RACE*AR		.08
RMSE	W	3.96
	B	4.07
RSQ	W	.07
	B	.15

Variables preceded by RACE epresent interaction terms
RMSE = Root Mean Squared Error
RSQ = Squared Multiple Corrleation Coefficient

Table 8

Tests of Differential Prediction Hypotheses
For Multiple Prediction Models

Air Force			Marine Corps		
Training Course	Ho: F	Coincident p value	Training Course	Ho: F	Coincident p value
Administrative Specialty			Clerical Specialty		
70230A	2.29*	.06	0151	.81	.52
70230B	10.32*	.00	2542	1.83	.12
70230C	1.19	.31	3043	.58	.68
73230	1.42	.23			
64530	.96	.43			
Electronics Specialty			Electronics Specialty		
42330	.22	.95	2531	.70	.62
42334	.63	.68			
42335	2.20*	.05			
46130	1.07	.38			
General Specialty			General-Technical Specialty		
63130	4.55*	.00	3371	5.26*	.00
27230	3.25*	.02			
62230	.49	.69			
64530	1.77	.15			
64531	1.76	.15			
29130	.27	.85			
90230	8.78*	.00			
90630	2.87*	.04			
98130	1.04	.37			
81132	5.11*	.00			
Mechanical Specialty					
42331	.75	.56			
42333	3.68*	.01			
42334	1.62	.17			
42335	4.76*	.00			
42632	.77	.54			
63130	1.57	.18			
46130	6.86*	.00			
43131	3.93*	.00			
43132	3.92*	.00			

*p < .10

Table 9A

Differences in Criterion Predictions (White-Black) Obtained
From Race-Differentiated Regression Equations
(Expressed in Black Standard Deviation Units)

Air Force

Administrative Specialty

Training Course	Predictor(s)	Point on Black Predictor Score Scale Mean - 1 SD	Mean	Mean + 1 SD
70230A	AIA	.20	.35	.51
	VE	.17	.29	.40
	NO	.29	.43	.57
	CS	.47	.49	.51
	Multiple	.01	.25	.50
70230B	AIA	-.03	.19	.41
	VE	-.12	.08	.28
	NO	.09	.23	.36
	CS	.13	.29	.46
	Multiple	-.33	.07	.47
70230C	AIA	.14	.21	.29
	VE	.06	.14	.23
	NO	.26	.34	.41
	CS	.24	.32	.39
	Multiple	-.07	.05	.16
73230	AIA	.14	.28	.42
	VE	.04	.18	.32
	NO	.28	.42	.56
	CS	.25	.37	.49
	Multiple	-.29	-.11	.08
64530	AIA	.03	.17	.31
	VE	-.01	.09	.19
	NO	.07	.19	.30
	CS	.06	.24	.42
	Multiple	-.20	-.05	.10

cont. Table 9A

Electronics Specialty				
Training Course	Predictor(s)	Point on Black Predictor Score Scale Mean - 1 SD	Mean	Mean + 1 SD
42330	AIE	-.10	-.02	.06
	AR	-.02	.14	.31
	MK	.26	.38	.49
	EI	.17	.23	.30
	GS	.02	.11	.20
	Multiple	.00	.08	.16
42334	AIE	.03	.13	.23
	AR	.10	.35	.60
	MK	.37	.56	.74
	EI	.03	.20	.37
	GS	-.06	.25	.55
	Multiple	-.04	.17	.39
42335	AIE	-.25	-.10	.05
	AR	-.03	.10	.22
	MK	.08	.15	.23
	EI	-.11	.11	.33
	GS	-.17	.10	.38
	Multiple	-.36	-.09	.18
46130	AIE	.04	.14	.23
	AR	.19	.31	.43
	MK	.31	.44	.57
	EI	-.07	.15	.37
	GS	-.04	.31	.66
	Multiple	.09	.27	.46

cont. Table 9A

General Specialty				
Training Course	Predictor(s)	Point on Black Predictor Score Scale: Mean - 1 SD	Mean	Mean + 1 SD
63130	AIG	.12	.17	.22
	VE	.07	.29	.51
	AR	.24	.25	.26
	Multiple	.06	.17	.27
27230	AIG	.10	.18	.26
	VE	.13	.32	.52
	AR	.25	.32	.39
	Multiple	-.02	.11	.24
62230	AIG	.00	.00	.00
	VE	.01	.13	.26
	AR	.15	.24	.32
	Multiple	.10	.14	.18
64530	AIG	-.09	-.07	-.05
	VE	.00	.10	.19
	AR	-.12	-.07	-.02
	Multiple	-.14	-.10	-.05
64531	AIG	-.23	-.16	-.09
	VE	-.20	-.05	.10
	AR	-.18	-.02	.15
	Multiple	-.29	-.14	.02
29130	AIG	.03	.03	.03
	VE	.11	.19	.26
	AR	-.03	.11	.24
	Multiple	.00	.01	.01
90230	AIG	.27	.29	.32
	VE	.28	.42	.55
	AR	.30	.43	.56
	Multiple	.30	.34	.38
90630	AIG	-.29	-.28	-.26
	VE	-.31	-.09	.14
	AR	-.16	-.18	-.19
	Multiple	-.30	-.24	-.17
98130	AIG	.06	.18	.30
	VE	.04	.17	.30
	AR	.18	.22	.26
	Multiple	-.06	.09	.24

cont. Table 9A

81132	AIG	.06	.10	.15
	VE	.05	.19	.33
	AR	.12	.27	.43
	Multiple	.02	.15	.29

Mechanical Specialty

Training Course	Predictor(s)	Point on Black Predictor Score Scale Mean - 1 SD	Mean	Mean + 1 SD
42331	AIM	-.34	-.17	.00
	MC	-.17	.01	.18
	GS	.00	.13	.27
	AS	-.25	-.06	.12
	Multiple	-.38	-.17	.05
42333	AIM	-.41	-.09	.23
	MC	-.18	.24	.66
	GS	-.13	.28	.70
	AS	-.18	.05	.28
	Multiple	-.62	-.02	.59
42334	AIM	-.36	-.14	.09
	MC	-.04	.12	.27
	GS	-.04	.26	.56
	AS	-.21	-.03	.16
	Multiple	-.36	-.07	.23
42335	AIM	-.48	-.28	-.08
	MC	-.13	-.04	.06
	GS	-.17	.10	.38
	AS	-.46	-.28	-.04
	Multiple	-.36	-.08	.21
42632	AIM	-.12	.02	.15
	MC	.08	.22	.37
	GS	.27	.47	.67
	AS	.10	.20	.30
	Multiple	-.15	.00	.15
63130	AIM	-.02	.05	.12
	MC	.21	.26	.31
	GS	.02	.26	.50
	AS	.00	.12	.24
	Multiple	-.01	.04	.09

cont. Table 9A

46130	AIM	-.70	-.29	.12
	MC	-.08	.08	.24
	GS	-.04	.31	.65
	AS	-.25	.01	.28
	Multiple	-.83	-.37	.10
43131	AIM	-.03	.13	.30
	MC	.30	.46	.62
	GS	.25	.42	.59
	AS	.10	.33	.56
	Multiple	-.04	.18	.39
43132	AIM	-.31	-.08	.15
	MC	.07	.25	.42
	GS	.07	.33	.59
	AS	-.08	.14	.35
	Multiple	-.22	.10	.42

Table 9B

Differences in Criterion Predictions (White-Black) Obtained
From Race-Differentiated Regression Equations
(Expressed in Black Standard Deviation Units)

Marine Corps

Training Course	Predictor(s)	Point on Black Predictor Score Scale: Mean - 1 SD	Mean	Mean + 1 SD
Clerical Specialty				
0151	CL	.25	.20	.15
	VE	.11	.09	.07
	NO	.13	.13	.13
	CS	.25	.14	.02
	Multiple	.11	.03	-.05
2542	CL	-.21	-.08	.05
	VE	-.45	-.31	-.17
	NO	.00	-.04	-.07
	CS	-.15	.02	.18
	Multiple	-.62	-.33	-.04
3043	CL	.13	.27	.40
	VE	-.02	.08	.18
	NO	.21	.30	.39
	CS	.19	.36	.52
	Multiple	-.12	.06	.24
Electronics Specialty				
2531	EL	.04	-.01	-.07
	AR	.09	.07	.06
	MK	.05	.09	.14
	EI	.03	-.08	-.18
	GS	.05	.00	-.05
	Multiple	.11	.02	-.06
General-Technical Specialty				
3371	GT	.45	.37	.29
	VE	.64	.49	.34
	AR	.39	.42	.45
	Multiple	.45	.34	.23

Appendix A

Consider the regression of Y on x for two independent groups. For each group (denoted by subscripts 1 and 2), the regression of Y on x is assumed to be linear and homoscedastic, with residual variance ϕ_i ($i = 1,2$). Also, the residuals are assumed to be independent and normally distributed. Initially, we wish to compare the predicted values on the criterion variable obtained from the within-group regression lines evaluated at a single point on the abscissa (denoted x_0). Starting with indifference prior distributions (uniform on the slope and intercept, log-uniform on the residual variance) the posterior distribution of the expected value of Y at x_0 for Group 1, conditioned on ϕ_1, is normal with mean $\bar{Y}_1 + \hat{B}_1(x_0 - \bar{x}_1)$ and variance $\phi_1 \left[\frac{1}{n_1} + \frac{(x_0 - \bar{x}_1)^2}{\sum_{i=1}^{n_1} (x_i - \bar{x}_1)^2} \right]$. ^ denotes the ordinary least squares estimate of the slope. Similarly for Group 2, the posterior distribution of the expected value of Y at x_0, conditional on ϕ_2, is normal with mean $\bar{Y}_2 + \hat{B}_2(x_0 - \bar{x}_2)$ and variance $\phi_2 \left[\frac{1}{n_2} + \frac{(x_0 - \bar{x}_2)^2}{\sum_{i=1}^{n_2} (x_i - \bar{x}_2)^2} \right]$. The marginal posterior distributions on the residual variances ϕ_1 and ϕ_2 are $\chi^{-2}(n_1 - 2, S_1^2)$ and $\chi^{-2}(n_2 - 2, S_2^2)$, respectively. S_1^2 and S_2^2 represent the sum of the squared residuals around the within group regression lines.

Under the assumption of equal residual variances for the two regression lines, i.e., $\phi_1 = \phi_2$, the marginal posterior distribution of the common residual variance ϕ is $\chi^{-2}(n_1 + n_2 - 4, S_1^2 + S_2^2)$ via the distributional theorem presented in Novick and Jackson (1974, p. 228). Conditional on the common, but unknown, residual variance ϕ, the distribution of the difference in predicted criterion values obtained from

the within-group regression lines evaluated at x_0 is normal with mean $\bar{Y}_2 - \bar{Y}_1 + \hat{B}_2(x_0 - \bar{x}_2) - \hat{B}_1(x_0 - \bar{x}_1)$ and variance

$$\phi\left[\frac{1}{n_1} + \frac{1}{n_2} + \frac{(x_0 - \bar{x}_2)^2}{\sum_{i=1}^{n_2}(x_i - \bar{x}_2)^2} + \frac{(x_0 - \bar{x}_1)^2}{\sum_{i=1}^{n_1}(x_i - \bar{x}_1)^2}\right].$$ Therefore, via the

distributional theorem presented in Novick and Jackson (1974, p. 229), the posterior marginal distribution of the difference in predicted criterion predicted values (at x_0) is 1) $t(n_1 + n_2 - 4, \hat{Y}_2|x_0 - \hat{Y}_1|x_0,$

$$(S_1^2 + S_2^2) \times \left[\frac{1}{n_1} + \frac{1}{n_2} + \frac{(x_0 - \bar{x}_2)^2}{\sum_{i=1}^{n_2}(x_i - \bar{x}_2)^2} + \frac{(x_0 - \bar{x}_1)^2}{\sum_{i=1}^{n_1}(x_i - \bar{x}_1)^2}\right]).$$ Expression 1 is,

in a standardized form, identical to the sampling distribution of the difference in criterion predictions obtained from the within-group regression lines evaluated at x_0.

Thus, when starting with indifference priors and under the assumption of unknown but equal residual variances, the $100(1 - \alpha)$ percent credibility interval for the difference in criterion predictions for the within-group regression lines evaluated at x_0 will coincide with what classical statistics calls a $100(1 - \alpha)$ percent confidence interval. Further, since x_0 may be any real number ($x_0 \in R$), this result will hold for all values of x.

In summary, under the assumption of an unknown but equal residual variance, the Bayesian approach to Johnson-Neyman technique (starting with non-informative priors) and the classical approach will yield identical results. This conclusion is valid only for what is referred to as 'non-simultaneous' confidence intervals in classical statistics. Asymptotically, the assumption of equal residual variances is not needed for the results of Bayesian and classical J-N analyses to converge.

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